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Contact Tracing With District-Based Trajectories

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ABSTRACT

Identifying the places an infected person has visited during a virus incubation time in order to conduct contact tracing is currently done using manual interviews since proximity-based contact tracing methods do not store geolocation information due to privacy concerns. During the incubation time, an infected person might visit several locations and either forget where they went or are reluctant to disclose their trip details. To minimize manual location tracing while preserving the user's privacy, the authors propose a mesh block sequence method where the trajectories are transformed into a mesh block sequence before being shared with health authorities. These simulations show that this a useful method by which to protect user privacy by concealing specific details related to a trajectory. While this simulation uses an Australian administrative region structure, this method is applicable in countries which implement similar administrative hierarchical building blocks.

KEYWORDS

Contact Tracing Query, District, Mesh Block Sequence, Privacy Protection, Trajectory Transformation

INTRODUCTION

Infectious diseases caused by pathogens can spread directly or indirectly from one person to another, similar to a chain reaction. When a pathogen infects a person, the time it takes for the symptoms to appear is called the incubation time or subclinical stage. The length of the incubation time differs from one pathogen to another. During this incubation, an exposed person should be in quarantine to prevent the spread of microorganisms (Virlogeux et al., 2015).

The incubation time for some pathogens may be as low as one day, but for others, the incubation time may be longer (CDC). For example, common cold-related viruses may have an incubation period of 1-3 days, an H5N1 virus for avian influenza has an incubation time of 2-5 days, whereas the COVID-19 virus may have an incubation time of up to 14 days. During the subclinical disease stage, an infected person might travel to various places, and the chance of spreading pathogens in the community is very high. The shorter incubation time for H5N1 resulted in this disease having

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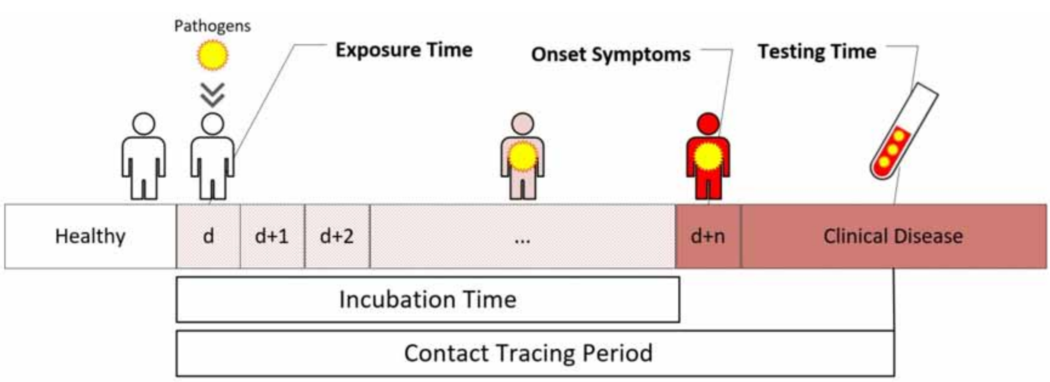
a high concentration only in Asia, while the longer incubation time for COVID-19 has resulted in this disease becoming a global pandemic. To control the outbreak, comprehensive testing, contact tracing, and isolation are mandatory when dealing with infectious diseases (Hellewell et al., 2020; Salathé et al., 2020).

Figure 1 shows the exposure and incubation time for an infectious disease. Since no symptoms are evident during the incubation time, the likelihood of early detection of the disease is low. Contact tracing must be undertaken when a person has tested positive for the infection, but the length of the incubation period may vary from case to case. The most difficult problem in the contact tracing procedure is obtaining accurate information on the places the infected person visited during the incubation as some people might be reluctant to reveal details of their whereabouts due to privacy concerns (Travers et al., 2020). Most countries had either limited or completely halted international and domestic flights by Q2-2020 to prevent the spread of new cases. Several countries also implemented additional strategies to control the spread of the COVID-19 pandemic, such as conducting intensive testing throughout the nation (Sonn, 2020), digitally tagging those suspected of being infected (Mozur et al., 2020), imposing strict lockdowns with curfews (9News Staff, 2020). However, some countries such as Sweden did not impose a strict lockdown for its citizens; rather, it recommended that people practice social distancing, wear masks and work from home where possible. However, business, retail, and schools remained open (Thomas, 2020).

The proximity-based approach as implemented in COVID safe (Ministry of Health Australia, n. d.; Ministry of Health Israel, n. d.) PEPP-PT (PEPP-PT, 2020), SafePaths (Raskar, n. d.; Allheeib et al., 2020), StayHomeSafe (The Government of the Hong Kong Special Administrative Region, n. d.), and TraceTogether (Singapore, n. d.), using short-range wireless technology to identify nearby devices. Recent collaboration between Google and Apple resulted in the development of a framework for an Exposure Notification system for privacy-preserving contact tracing to overcome communication problems between two different platforms (Apple, n. d.). However, a recent report suggests that around 60% of the population must use a contact tracing app to ensure the system's effectiveness (Hinch et al., 2020). In Australia, despite the high number of COVID-19 cases, the COVIDsafe app has provided little assistance to health authorities, and the number of users of this application is still below the minimum required number (Meixner, 2020).

The trajectory-based approach implements a spatial indexing concept such as R-Tree, Quad Tree or a hybrid tree to group trajectories and simplifies the findings of specific trajectory points and other nearby trajectories at a particular time (Ali et al. 2020; Li & Shin, 2018). In this approach, the trip details are indexed in the server for processing when required. However, since users must share details on their entire trip, trajectory-based methods result in problems with privacy issues.

Figure 1.
Exposure and incubation time



To address the problem of missing visited locations while preserving users' privacy and providing sufficient detail to the authorities, we propose a district-based contact tracing method that substitutes trajectory details with a district sequence (DS). In summary, we describe the contributions of our works as follows:

1. We propose a MBS as a substitute for the user's trajectory to be shared with government and health authorities where the MBS can replace the places visited by the person without exposing the specific details, while maintaining the accuracy needed by the authorities.
2. We propose a district-based contact tracing query as an alternate solution for the contact tracing problem during incubation.
3. We demonstrate the effectiveness of MB-CTQ in identifying the places visited, the times these places were visited, and other persons who might be at risk when visiting unsafe MBs.

Our simulation shows that this method can identify the possible contact areas from a trajectory and find persons who encountered the infected person. Although this method is limited as it uses the Australian region boundary model, this model is highly applicable in other countries which implement similar administrative building blocks.

RELATED WORKS

Proximity Approaches

During a pandemic, contact tracing is the most important step in identifying the places an infected person visits and the people with whom they have come in contact during the incubation time (Ferretti et al., 2020). The COVID-19 virus can be transmitted to another person who is located within the 1.5m - 2m range of a COVID-19 infected person; therefore, a proximity-based detection approach using Bluetooth Low Energy (BLE) from a smartphone is utilized for many contact tracing methods and apps. Since privacy is the main issue in a contact tracing system, many studies have been undertaken to overcome this problem using a decentralized system where the data is stored in the user's device. To secure the data, several methods are implemented, such as a hash table in CAUDHT (Brack et al., 2020), pseudonyms in PACT (Chan et al., 2020), minimizing the data in DP3T (Vaudenay, 2020), or an anonymized graph (Yasaka et al., 2020). To address several technical issues, Google and Apple collaborated to build a multi-platform API that enables apps created by health authorities to work more accurately, reliably, and effectively across Android phones and iPhones (Bogle & Borys, 2020).

Most proximity-based contact tracing apps do not record the locations visited due to privacy issues (Raskar et al., 2020; Reichert et al., 2020). Several sources can be used to obtain this information, such as manual interviews, cellphone-location data, credit-card records, and CCTV (COVID-19 National Emergency Response Center and Epidemiology & Case Management Team Korea Centers for Disease Control & Prevention, 2020). However, obtaining historically visited places is difficult because people might not be willing to divulge their travel details.

Spatial Indexing Model

Another contact tracing approach is using the person's historical trajectory data extracted from their mobile phone. Although a trajectory is considered a private record, a smartphone as a daily companion might be subjected to several privacy threats, such as geotracking on photos and apps, mobile keylogging, malicious apps, eavesdropping, and backdoor threats (DeMuro, 2018; Stegner, 2018). Therefore, using the user's trajectory as a data source for contact tracing will not introduce new privacy issues. Moreover, during a pandemic, a person must leave their contact details when visiting a shop or restaurant so the health authorities can contact those in the same location as someone who has tested positive for the virus.

Trajectory data have been widely used for spatial analysis problems, such as data mining for movement patterns (Taniar & Goh, 2007; Zheng, 2015), estimating urban movement (Iwata et al., 2017), traffic modelling (Xu et al., 2019; Zhao & Shi) and contact tracing (Kim et al., 2020; S et al., 2020; Vogt et al., 2021).

To handle the large number of trajectories, several indexing methods have been proposed to improve the processing performance, such as R Tree-based in MVR Tree (Hadjieleftheriou et al., 2006) or R Query (Zheng, 2011), Quad Tree-based in TQ Tree (Ali et al., 2018), TPR*-Tree (Li & Shin, 2018), and a combination of R-Tree and Quad Tree in QR-Tree (Ali et al., 2018) as shown in Figure 2. Other methods that can be used are the grid system using MGRS (Mariescu-Istodor & Fränti, 2017), or polynomial approximations (Ni & Ravishankar, 2007). Figure 2(a) shows a MVR-Tree using temporal elements in creating the R-Tree to capture and index the object's movement; hence, the MBRs are transformed into a three-dimensional block. The Trajectory Quad-Tree (TQ-Tree) uses different approaches in handling the trajectories, where the trajectories with close spatial proximity and similar orientation are grouped.

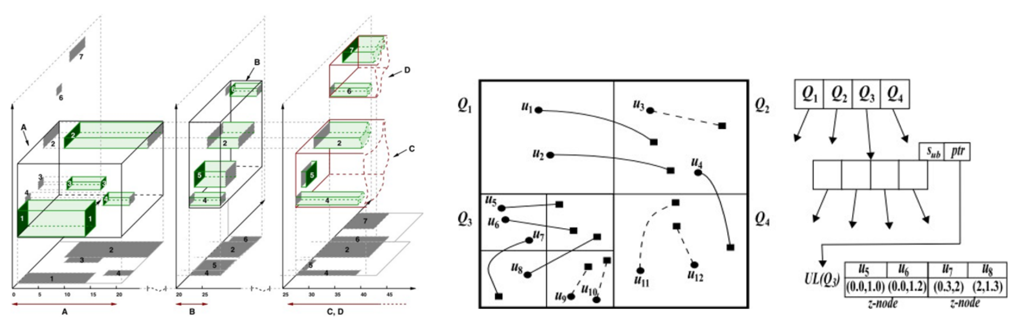
A spatial indexing model is used to manage trajectory data so that query retrieval for a specific trajectory point at a particular place and time will be efficient. In contact tracing, finding other persons who have been at the same place at the same time as an infected person is key to limiting the spread of a virus. While the method is useful for contact tracing, sharing trip details with the authorities might raise privacy concerns for users.

Privacy Issues

While spatial-based trajectory indexing methods perform well, these methods do not identify the visited objects, which is one requirement for contact tracing. One of the principal aims of contact tracing is to identify all the places an infected person visits during a trip. Since revealing geolocation for contact tracing might raise privacy issues, several methods have been developed to hide the person's real identity or location, such as FakeMask to generate fake context (Zhang et al., 2016), KAT to replace real locations with dummy locations (Liao et al., 2015), PLQP (Li & Jung, 2013), or Landmark Tree (Shao et al., 2015).

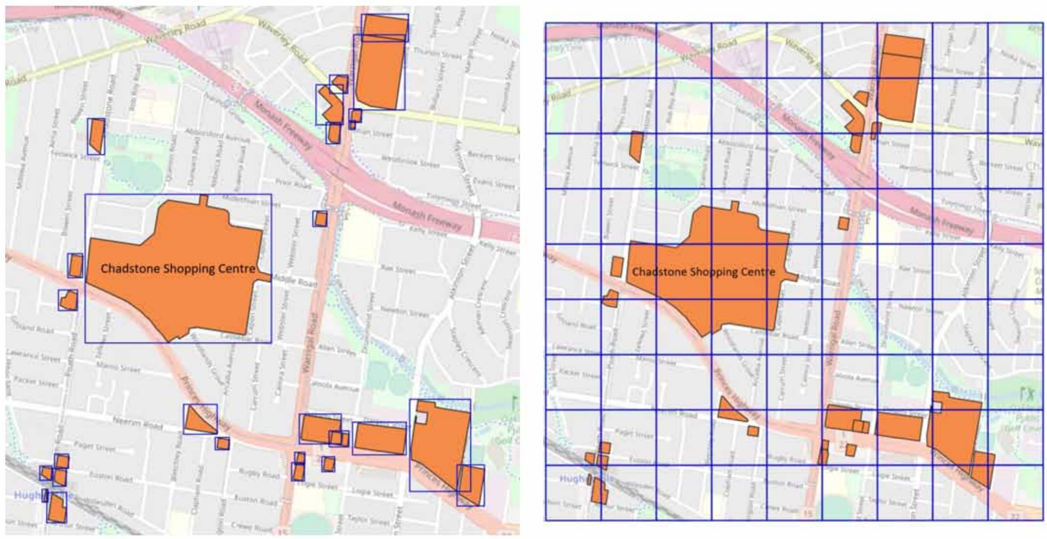
In the contact tracing procedure, the area name can substitute the coordinates of a trajectory point. The renaming is because the red zone status refers to the area instead of the coordinate itself, as shown in Figure 3a. This figure uses a minimum bounding rectangle (MBR) to represent a commercial building on a map. While an MBR might appropriately represent a commercial place, the coverage of MBR is limited to the object itself. For example, if the infected person also visited a place outside the Chadstone shopping centre, the location would not be recognized even though the area is still inside the MBR of the Chadstone shopping centre.

Figure 2.
Example of trajectory indexes



(a) MVR Tree (Hadjieleftheriou et al., 2006)   (b) TQ-Tree Index (Ali et al., 2018)

Figure 3.
Object representation



(a) MBR-based (b) Grid-based

To cover the entire map, a grid method can represent the object. The gap problem in the MBR approach can be solved using a grid model, where the idea is to split the area into uniform cells to cover the entire(Allheeib et al. 2022; Mariescu-Istodor and Fränti 2017), as shown in Figure 3b. The entire map is covered in a grid model with no visible gaps. However, three problems might arise from this approach. First, the size of the places is not uniform, and several cells may be required to cover the entire location. Second, the accuracy of the grid depends on the cell size, which differs from one location to the other. Third, it is difficult to identify the exact location name from the grids.

To overcome the object representation problem, we propose a mesh block-based tracing method that uses mesh blocks to represent real-world objects. The detailed trajectories are transformed into a mesh block sequence (MBS) to protect the users' privacy, where the MBS is used for the contact tracing process.

MESH BLOCK SEQUENCE FOR CONTACT TRACING

For contact tracing, it might not be necessary to reveal the real geolocation (coordinates) a person has visited recently or the entire trajectory. Since pathogen transmission only occurs during close contact (while a person is walking), there are three vital pieces of information that need to be obtained from a trajectory for contact tracing:

1. Identify the part of the trajectory that contains walking state.
2. Retrieve the area and time window where walking condition occurs
3. Identify other users in the same area at the same time as the infected person.

While pathogen transmission only occurs within a specific distance, in this paper, we do not consider proximity since we focus on identifying the location name considering the infected person can move anywhere and avoiding the proximity-detection problem.

For example, the recent outbreak in Victoria occurred in a Chadstone shopping centre butcher shop and was linked to several infected households (Zagon, 2020). When an infected person visits a shopping centre by car, the main concern is to identify the place where this person got out of their car and where they walked. Furthermore, instead of reporting that this person visited the butcher shop in the Chadstone shopping centre, he can say that he went to Chadstone shopping centre since his walking path from the car park to the butcher shop is unknown. Therefore, health authorities should report that an infected person visited the Chadstone shopping centre rather than only mentioning one specific shop.

Figure 4 shows the principal idea of our proposed method. As shown in this figure, a person travelled to a shopping centre from his home by car. During his trip to the destination, he made a short stop at a petrol station and continued his trip to the shopping centre. Finally, he parked his car in the car park and walked into the shopping centre. On this journey, he could have possibly infected other people where he was not in his vehicle, as indicated by the red zones. The sequence for this journey is: home –> petrol station –> shopping centre. In this example, we only need these parts for contact tracing.

Australian Statistical Geography Standard

The Australian Statistical Geography Standard (ASGS) provides a framework of statistical areas used by the Australian Bureau of Statistics (ABS) and other organisations to enable the publication of statistics that are comparable and spatially integrated (Australian Bureau of Statistics, 2016). A district or mesh block (MB) is one of the main ABS structures where the purpose is to provide standard area granularity throughout the country. The ABS structure has seven hierarchical levels where smaller regions are combined to build up a larger area. The ABS structure and examples of shopping centres around Chadstone in various ABS structures (MB and SA1) are shown in Figure 5. In this example, the Chadstone shopping centre is represented as MB 2055600000.

Mesh blocks are the smallest polygon in the ABS structure identifying land use. 358,122 MBs cover the entirety of Australia without gaps or overlaps. On average, each Mesh Block will contain 30-60 dwellings. On average, each MB contains 30-60 dwellings. Urban MBs follow main roads or rear property boundaries wherever possible to ensure the neighborhood remains intact. MBs identify major facilities, such as hospitals, shopping centres, educational institutions, and transportation hubs. A single MB reflects the land use in this area, namely residential, commercial, industrial, parkland, education, hospital/medical, transport, primary production, water and other land use. Each MB is identified by an 11-digit unique ID that contains the State/Territory identifier (1 digit) and MB identifier (10 digits). We show an illustration of land use in Figure 6.

In summary, we use Mesh blocks as the foundation for our contact tracing because:

1. Mesh blocks cover entire Australia without gaps and overlaps.
2. Each mesh block has a unique identifier

Figure 4.
Trajectory parts

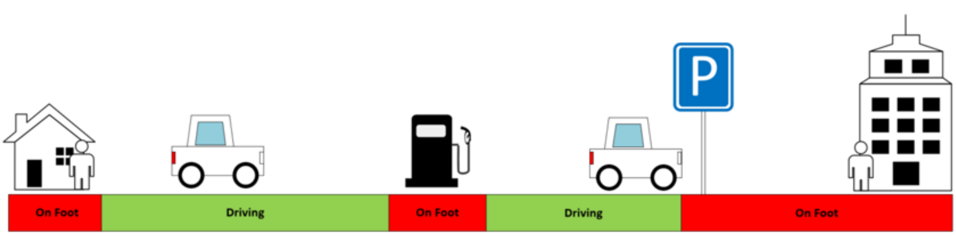


Figure 5.
ASGS ABS structures

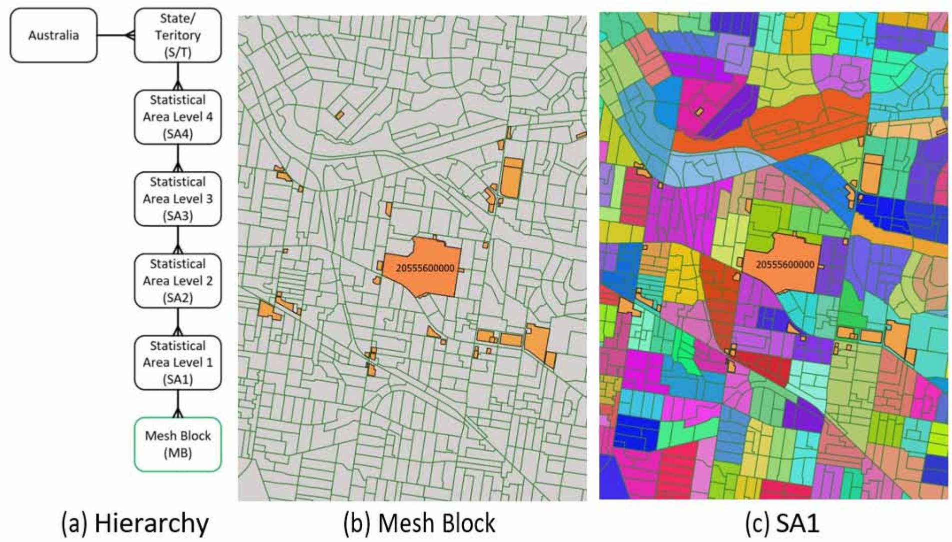


Figure 6.
Map representing mesh blocks

3. Each mesh block serves a specific land use, for example, shopping centre, hospital, university or sports centre.
4. Road network is covered in a mesh blocks polygon.

Trajectory

Trajectory or GPS traces are a collection of s user's position p in a time interval or speed interval where $T = \{p1, p2, ..., pn\}$. A trajectory can be obtained by utilizing a GPS-enabled device, such as a smartphone, to record movement and store the information in local or cloud storage. A trajectory file may contain numerous trajectory points, each with attributes or tags describing the geolocation condition.1 The most common tags are coordinates (latitude, longitude), elevation and time. In addition, some trajectories have a time zone indicator in the tag such as +11:00 for AEST during daylight savings, while some trajectories denote the time in UTC format.

Concerning contact tracing, an exposed person is considered to have a high probability of spreading the virus if he comes into close contact with other people while walking. It is not possible to know a person's mode of transportation from the raw trajectory data; however, we can infer whether they are walking, cycling, or driving by calculating their speed at each trajectory point.

Definition 3.1. Point Velocity ($V(pi)$) Let $pi-1$, pi Î T be the trajectory points of T in chronological order. Point Velocity $V(pi)$ is the speed of trajectory point pi relative to the previous trajectory point $pi-1$, which can be shown as:

$$V\left(p_i\right) = \frac{d\left(p_i, p\left(i-1\right)\right)}{time\left(p_i\right) - time\left(p_{(i-1)}\right)} \tag{1}$$

Definition 3.2. Movement Mode M (pi) represents the estimated transportation mode used at a certain trajectory point pi based on $V(pi)$. Movement Mode is the walk point when $V(pi)$ is within the walking speed threshold vw. The Movement Mode is the vehicle point when $V(pi)$ exceeds vw.

$$\frac{M\left(p_i\right)}{Vw} = \frac{\boldsymbol{f}_{WalkPoint\left(WP\right), \quad if\ 0 \le |V\left(p_i\right) \le}}{VehiclePoint\left(VP\right),\ otherwise} \tag{2}$$

To explain Definition $3_{.2}$, consider the following example in Figure 7 that shows a trajectory that starts at MB 20552100000 and ends at MB 20552813000. The average walking speed threshold vw is 5km/h, the blue dots represent all the vehicle points (VP), and the red dots represent the walk points (WP). Although we can see that there are some incorrect tags at the intersection, these points can be filtered out in the next step.

Mesh Block Sequence

In this subsection, we will discuss the transformation of trajectory data to a Mesh Blocks Sequence (MBS) to protect user privacy while sharing details on their trips with the health authorities for contact tracing purposes.

Definition 3.3. An MBS is the set of visited MBs representing the trajectory path chronologically. The time a trajectory point enters an MB is called entry time te, while the time for the last trajectory point stays in the same MB is called exit time tx.

Definition 3.4. Reduced Mesh Block Sequence (RMBS) is a subset of MBS where for each MB, the occurrences of WP must be higher than the walk point number threshold σWP, where åWP3 σWP.

We demonstrate the transformation of MBS to RMBS in Table 1. As shown in the example in Figure 7, the MBS for trajectory T is the set of MB in chronological order as follows: MBS (T) = {20552100000, 20552910000, 20556522000, 20556523000, 20556522000, 20551070000, 20552811000, 20552814000, 20552813000}. We then populate the statistical data in each MB and present the MBS in Table 1a. The average speed $V(p)$ for each MB is set to km/h. We disregard the entry time and exit time for the sake of simplicity. As can be seen from this table, Mesh Block

20556522000 occurs twice as the user visited the same MB at different times.

Figure 7.
Example of a mesh block trajectory

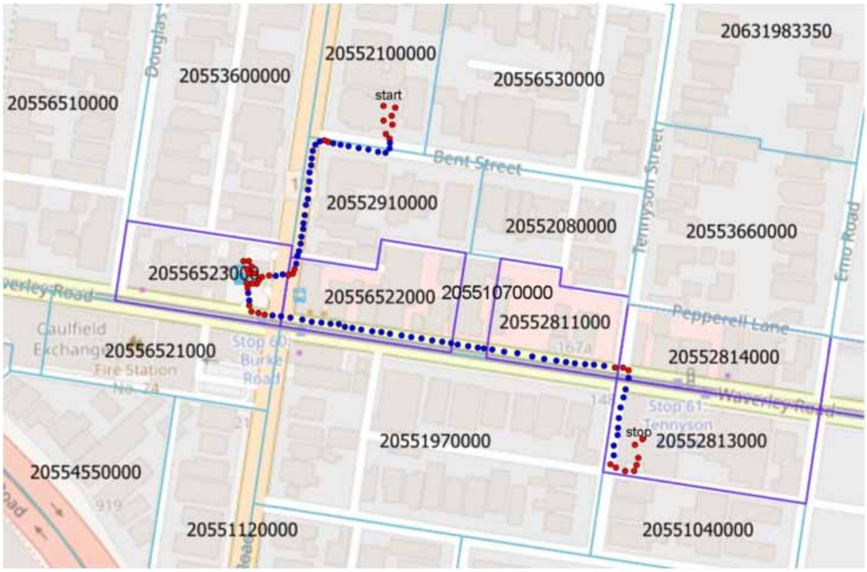


Table 1.
Example of MBS to RMBS

(a) MBS Table					
MB	***te***	***tx***	***åW P***	***åV P***	***V (p)***
20552100000	.	.	7	2	4
20552910000	.	.	2	24	28
20556522000	.	.	3	1	12
20556523000	.	.	16	6	3
20556522000	.	.	0	18	29
20551070000	.	.	0	4	27
20552811000	.	.	1	11	25
20552814000	.	.	2	1	9
20552813000	.	.	8	8	17
(b) Reduced MBS table σW P = 5					
MB	***te***	***tx***	***åW P***	***åV P***	***V (p)***
20552100000	.	.	7	2	4
20556523000	.	.	16	6	3
20552813000	.	.	8	8	17

During a trip, travelling speed is never constant. A mesh block is considered to be the walking area if there are at least $\sigma W P$ number of $W P$ occurrences in a single visit. An MBS table which only contains the MBs that satisfy this condition is called a Reduced MBS (RMBS). The RMBS table is shown in Table 1b.

Algorithm 1.
Mesh block sequence transformation

Require: Trajectory $T = \{p1, p2, .., pn\}$,
Walk speed threshold vw,
Walk point count threshold σWP,
MBDataset MBD
Ensure: MBS
1: **for** all T do
2: $\boldsymbol{p_i}$ $\boldsymbol{.v}$ ¬ $getSpeed$ ($_{pi}$, p (i−1))
3: pi $.mode$ ¬ $se_{tM}ode$ ($_{pi,\ v,}$ vw)
4: $_p i$ $.MB$ ¬ $getMB$ (pi, MBD)
5: MBS $_{.a}ppend$ ($p_{i)}$
6: end $_f$or
7: $CalculateStatisti_c$ (MBS)
8: $RMBS$ ¬ $Reduced$ (MBS, σWP)

The algorithm to transform GPS traces into an RMBS is presented in Algorithm 1. In this algorithm, lines 1-5 calculate the trajectory point velocity, identify the movement mode and obtain the associated MB after which the MBS statistic is calculated and the MBS is reduced by applying a specific threshold σWP.

Mesh Blocks-Based Contact Tracing Queries (MB-CTQ)

A Mesh Block-based Contact Tracing Query (MB-CTQ) is a method to perform contact tracing query on RMBS dataset, where the dataset only contains all the MBS for a walking movement, and the minimum number of walk points is σWP. There are two types of MB-CTQ queries as follows:

(1) To identify all MBs and the time an exposed person has visited when walking. These MBs are called Unsafe MBs.
(2) To obtain all the trajectories of peop**le who hav**e visited the Unsafe MBs when walking.

The first query obtains all the MBs and the time an exposed person has been during his incubation period. This query will retrieve all the MBS for this particular user that satisfy minimum σWP. These MBs will be tagged as Unsafe MBs for a specific period.

The second query retri*eves all u*sers with Unsafe MBs in their trajectory trips. We call this list of users level-1 spreaders since these users may have had a close contact encounter with the exposed person. Therefore, it is necessary to obtain all level-1 users' trajectories as well and identify all possible Unsafe MBs to extend the search for level-2 spreaders. However, this query only retrieves level-1 users with unsafe MBs in their MBS trips.

The MB-CTQ model transforms trajectories into RMBS to ensure user privacy while also providing adequate details to the health authorities. The users only share RMBS with the authorities while the detail of the trajectories remain in the users' personal devices. The contact tracing process is performed on the RMBS database. A detailed investigation of a specific place in a mesh block area can be further conducted with the user when needed.

EXPERIMENTS AND EVALUATIONS

In this section, we evaluate the efficiency of MB-CTQ in identifying Unsafe MBs and check the other trajectories of people who have visited Unsafe MBs. We modify the GPX dataset from planet.gpx2 to ensure all the trajectories share a similar trav[e]lling time to simulate the massive movements in the 850 km2 of Melbourne metropolitan area. For these experiments, we processed 300+ trajectories from various contributors. Then, we transformed the trajectories into RMBS for a day trip. Our methods are implemented in a system running Java with PostGIS as the database engine.3 For the visualization tool, we use QGIS.4 The system uses Intel i7-8665U CPU with 16GB of RAM. As a comparison, we undertake the evaluation by comparing MBS with grid sequence (GS).

The MB size variations are shown in Figure 8. While most MBs are between 0.01 km^2 until 0.03 km^2 in size, the average size for an MB is 0.03 km2. Hence, our grid size is set to 0.03 km^2 to match the average MB size.

Identify Walking Points

In this evaluation, as an example, we assume trajectory number 000509760 belongs to an exposed person. Since there is no information on his transportation mode, we assume from his trajectory path and speed that he used a bicycle as his transportation mode where he travelled at >20km/h on the road. As the normal walking speed is around 5 Km/h, we set the walking speed threshold $V(p)$=8 Km/h to also accommodate a faster walking speed. Therefore, all the velocity points beyond this limit are considered a non-walking mode, while we consider all the points below this velocity limit a walking mode.

The trajectory and the respective MBS are shown in Figure 9. From the timeline in Figure 9b, it can be concluded that the person made the trip in the morning between 8AM to 10AM across 105 mesh blocks. The red points along the track indicate the walking points in this trajectory.

Figure 8.
Mesh block size variation

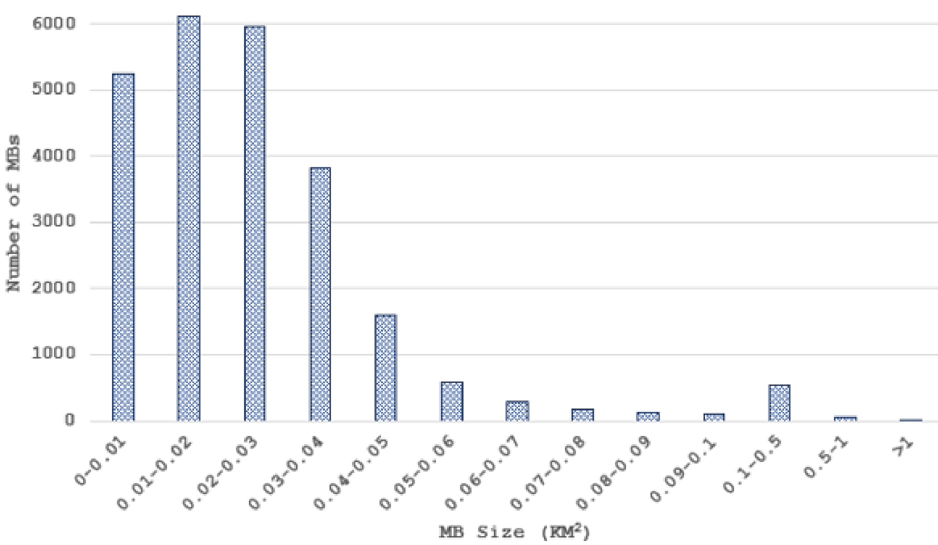
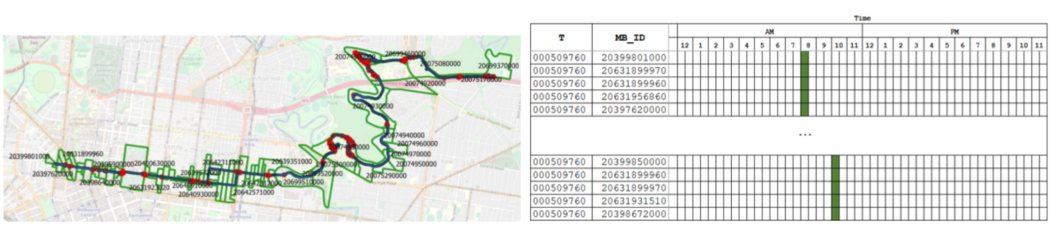


Figure 9.
Example of trajectory to MBS



(a) MBS with Trajectory Path (b) Mesh Block Sequence Timeline

Figure 10 shows the trajectory, the walking points as indicated by red points, and the occupied grids. Like the MBS in the previous figure, the GS also shows that the person undertook his trip in the morning between 8AM to 10AM across 257 Grids.

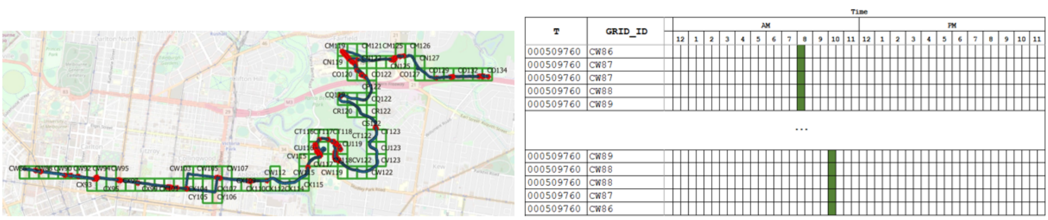
Although the MBS timeline shows similarities with the GS timeline, the number of objects that need to be processed in MBS is half that of the GS. The consequences of this are discussed in the next part of our evaluation section.

Identify Unsafe Areas

To identify the unsafe MBs, we eliminate all that do not contain a walking mode trajectory point since pathogen transmission is only possible when a person moves at walking speed. In some circumstances, a vehicle might need to slow down to a walking speed because of several traffic conditions. However, a slow trajectory point might not dominate all the other trajectory points at a specific MB unless there is a massive traffic jam, as shown in Figure 11.

In this evaluation, the minimum number of walking points for each area is 5 $\sigma WP = 5$. Therefore, any MBs or grid cells that contain less than 5 walking points are not considered to be an unsafe area.

Figure 10.
Example of trajectory to grid



(a) Grid Sequence with Trajectory Path (b) Grid Sequence Timeline

Figure 11.
Predicted walking point due to traffic light

To obtain RMBS, we filter out MBs that have the walking points less than σWP. The RMBS path and its timeline are shown in Figure 12. The RMBS table in Figure 12b answers the first contact tracing query, where the aim is to identify all the unsafe MBs.

The unsafe cells in reduced grid sequence (RGS) are obtained by removing all the cells from the GS with walking points less than σWP. The result in RGS and the RGS Timeline are shown in Figure 13. In this evaluation, RMBS have less entry of 24 unsafe MBs than RGS with 35 cells.

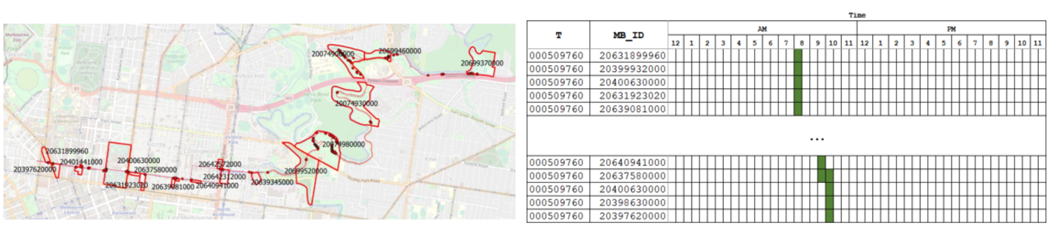
Identify Unsafe Users

We further investigate MB 20400630000 as an example of an unsafe mesh block, where this MB represents the Melbourne Museum, Royal Exhibition Building and the Carlton Gardens, as shown in Figure 14. The first line in Figure 14b indicates the infected user's trajectory, while the yellow block indicates the time window when the person visited the premise. From the timeline table, we can see that over this time, eight other trajectories went to the same place at a similar time window. If we enlarge the time window to the AM/PM part, eleven trajectories went to the unsafe MB at the same time window as the infected person. This means that eight persons are in the same location and time as the infected user during this period. Therefore, these eight persons need to be tagged as potentially infected persons.

Figure 15 shows three unsafe cells with the respective reduced grid sequence timeline. Using a GS shows that eleven people entered unsafe cells during the same time window as the infected person. Trajectory 000554340 and 000578386 are partially included in the list since not all the cells are in the time window. The problem of partial inclusion is that unsafe cells only cover a small area. The small coverage causes these cells to include walking points that are located outside of the expected premise.

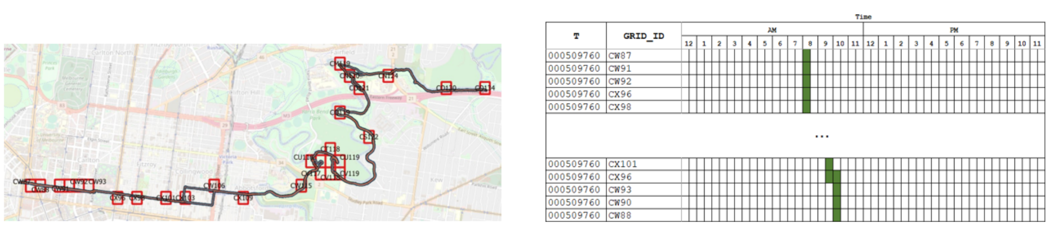
Although GS can also identify an unsafe area, interpreting the cells concerning the respective places or locations might need further processing effort. For example, the grid size might differ from place to place. Using a standard region boundary from the authority will make interpreting the site easier during the contact tracing process and minimize the user's privacy issues.

Figure 12.
RMBS where $\sigma WP = 5$



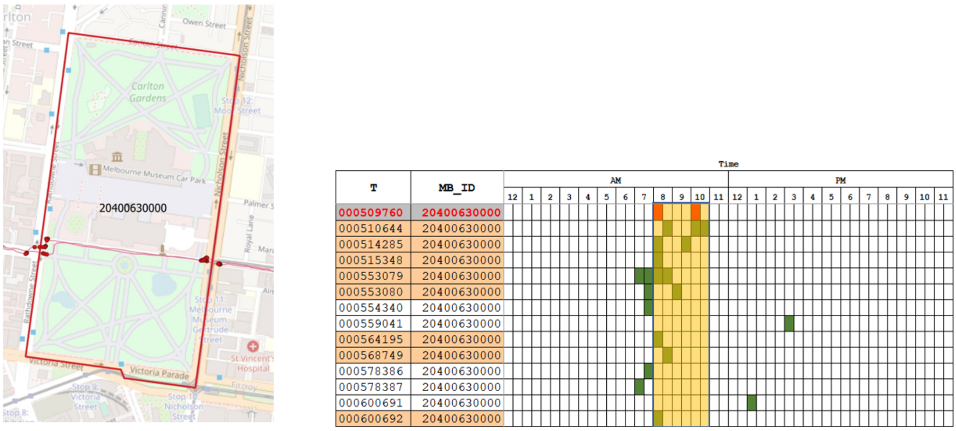
(a) RMBS map (b) RMBS Timeline

Figure 13.
RGS where $\sigma WP = 5$



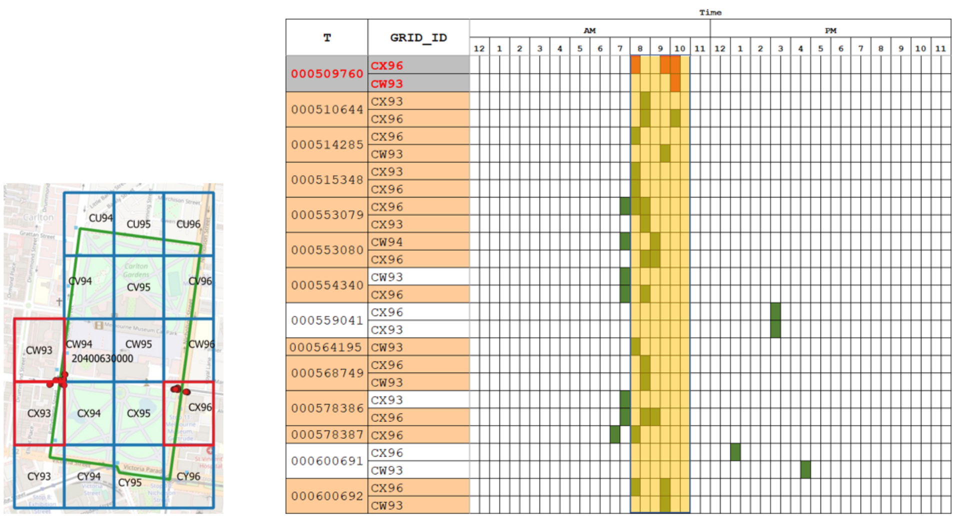
(a) RGS map (b) RGS Timeline

Figure 14. Unsafe MBs for other users



(a) MB map (b) Unsafe MBs Timeline

Figure 15.
Unsafe cells for other users



(a) Grid map (b) Unsafe Cells Timeline

Comparison Analysis

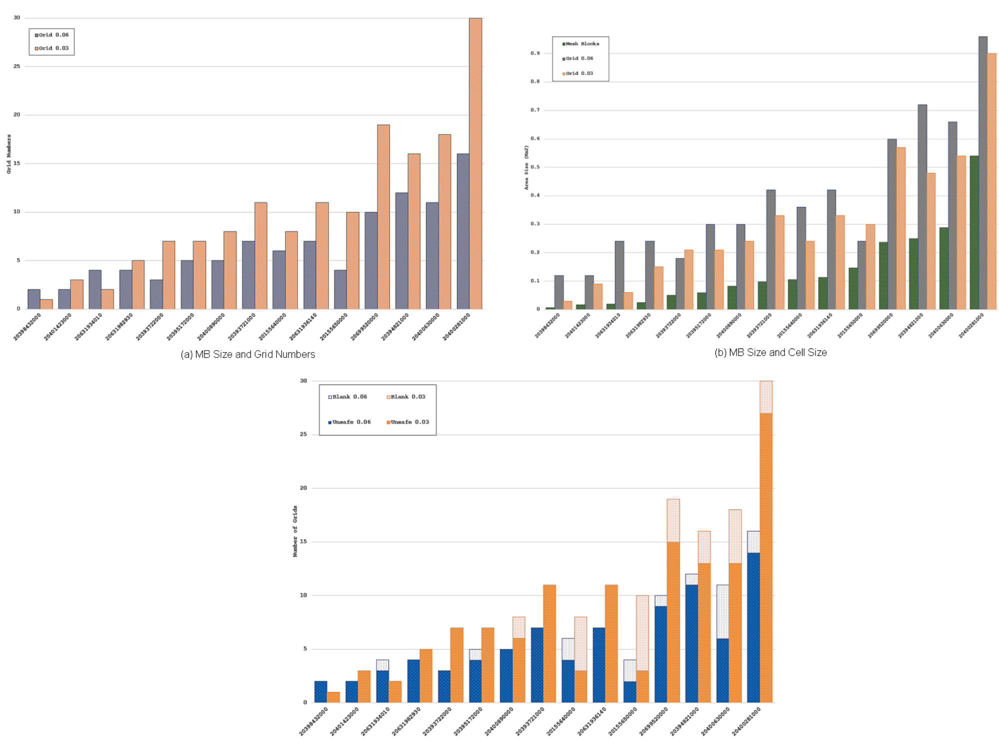
In this section, we compare the efficiency of the mesh block-based and grid-based methods of covering various places around Melbourne. We select several types of places, such as an educational institution, a shopping centre, a park, a health care facility, and a hotel. These places are sorted by area size in km2, as shown in Table 2. We create a grid in 0.03 km2 and 0.06 km2, indicated by Gx . The number of cells and size are shown in the table as well.

Figure 16 compares the size of the MBs and grids for all the places listed in Table 2. The first comparison is the relationship between mesh block size and the number of cells required to cover the whole MB. As seen in Figure 16a, the number of grids increases when the mesh block size is larger, although, in some circumstances, a larger area does not always mean a higher number of cells. This

Table 2.
MBS table

MB	Place Name	*AMB*	*åG0.03*	*A0.03*	*åG0.06*	*A0.06*
20398432000	RMIT Building 51	0.0064	1	0.03	2	0.12
20401423000	Mercure, Ibis Hotels	0.0171	3	0.09	2	0.12
20631934010	Royal Dental Hospital	0.0192	2	0.06	4	0.24
20631982930	Melbourne Central Station	0.0238	5	0.15	4	0.24
20393722000	Melbourne Aquarium	0.0503	7	0.21	3	0.18
20395172000	Southern Cross Station	0.0595	7	0.21	5	0.3
20400890000	The Royal Melbourne Hospital	0.0827	8	0.24	5	0.3
20393721000	Flinders Station	0.0971	11	0.33	7	0.42
20155640000	Northland Homemaker Centre	0.106	8	0.24	6	0.36
20631936140	Crown Towers Hotel-Casino	0.1128	11	0.33	7	0.42
20155650000	Bunnings Warehouse Northland	0.1468	10	0.3	4	0.24
20699520000	Studley Park Golf Course	0.2365	19	0.57	10	0.6
20394821000	South Wharf	0.2497	16	0.48	12	0.72
20400630000	Royal Exhibition Building & Melbourne Museum	0.2876	18	0.54	11	0.66
20400281000	University of Melbourne	0.5403	30	0.9	16	0.96

Figure 16.
MB and grid



inconsistency is because of non-uniform place sizes and the city layout, where the city blocks are arranged -7° parallel to the equator.

A comparison of MB size and the size of the total cells is shown in Figure 16b. Like the previous result, cell size increases linearly with mesh block size. However, due to the different granularity size, a smaller granularity might not occupy a larger size. As shown in this figure, *G*0.03 has a smaller total size compared to *G*0.06.

The grid-based approach can also cover places without a gap, however, not all cells in the grid-based method have walking trajectory points and can be considered an unsafe area, as shown in Figure 16c. Nevertheless, based on our evaluation, the mesh block-based method is suitable for hiding the details of a trajectory to preserve user privacy while providing adequate details to the authorities to perform contact tracing.

CONCLUSION

In this paper, we proposed a mesh block-based contact tracing query that uses MBS to replace a user's trajectory to minimize a breach of privacy while providing sufficient detail to the government and health authorities to perform adequate contact tracing during a pandemic. Although this method is specifically built using the Australian Statistical Geography Standard, this concept is highly adaptable to other locations which implement similar administrative hierarchical building blocks.

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ENDNOTES

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